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EXAMINER	
SPOONER, LAMONT M	
ART UNIT	**PAPER NUMBER**
2626	

DATE MAILED: 11/08/2006

Please find below and/or attached an Office communication concerning this application or proceeding.

Office Action Summary	Application No.	Applicant(s)	
	09/607,786	GAO ET AL.	
	Examiner	Art Unit	
	Lamont M. Spooner	2626	

-- *The MAILING DATE of this communication appears on the cover sheet with the correspondence address* --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on *16 August 2006*.

2a)☒ This action is **FINAL**. 2b)☐ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *1,3-6,10-19 and 28-44* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1,3-6,10-19 and 28-44* is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on *30 June 2000* is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)
2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
3) ☐ Information Disclosure Statement(s) (PTO/SB/08) Paper No(s)/Mail Date _____.
4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .
5) ☐ Notice of Informal Patent Application
6) ☐ Other: _____.

DETAILED ACTION

Response to Arguments

1. Applicant's arguments filed 8/16/06 have been fully considered but they are not persuasive. More specifically, regarding applicant's arguments "Bangalore merely describes a 'close relationship'...not the calculation of similarity within a sequence of training units." The Examiner cannot concur, as previously cited, Bangalore explicitly teaches, C.3.lines 22, 23, "The similarity between two words may be measured...", see also C.4.Table 2. Regarding applicant's arguments, "Bangalore shows forming a root cluster, not determining a frequency of occurrence of segments...", however, Bangalore teaches, as recited in the previous rejection, "Thus, the tree structure maintains ...all clusters and input words", see also C.3.lines 1-5, which teaches of the frequency space of these words, which inherently involves the frequency of occurrence of segments, see also C.2.lines 26-67.

2. In response to applicant's argument that there is no suggestion to combine the references, the examiner recognizes that obviousness can only be established by combining or modifying the teachings of the prior art to produce the claimed invention where there is some teaching, suggestion,

or motivation to do so found either in the references themselves or in the knowledge generally available to one of ordinary skill in the art. See *In re Fine*, 837 F.2d 1071, 5 USPQ2d 1596 (Fed. Cir. 1988)and *In re Jones*, 958 F.2d 347, 21 USPQ2d 1941 (Fed. Cir. 1992). In this case, Ramaswamy explicitly teaches clustering, and Bangalore explicitly provides an efficient method of clustering, see previous rejections. Therefore the suggestion, and motivation to combine become apparent as set forth in the previous rejection.

Applicant's arguments with respect to the claims in light of the newly added limitation regarding, "Dynamic Order Markov Model (DOMM)" have been considered but are moot in view of the new ground(s) of rejection. Furthermore the Examiner notes an absolute disconnection between the newly added limitations (see claims 1, 28 and 36) and the claim as previously presented, rendering correlated arguments misleading and confusing.

Claim Rejections - 35 USC § 103

3. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the

invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

4. Claims 1, 3-6, 14-19, 28-30, 33, and 35-39 are rejected under 35 U.S.C. 103(a) as being unpatentable over Ramaswamy et al. (U.S. Patent No. 6,188,976 filed Oct. 23, 1998) in view of Law et al. (Law, N-th Order Ergodic Multigram HMM for Modeling of Languages without Marked Word Boundaries).

As per **claims 1, 18, 19, and 28** Ramaswamy et al. discloses a method of using a tuning set of information to jointly optimize the performance and size of a language model, comprising:

segmenting at least a subset of received textual corpus into segments by clustering every N-items of the received corpus into a training unit (C.6.lines 15-18), wherein resultant training units are separated by gaps (C.6.line 67, C.7.lines 1, 2-the separate classes inherently includes gaps, C.6.lines 15-18-Fig. 5-item 40'-the separate sub-corpora inherently include gaps);

and wherein N is an empirically derived value based, at least in part, on the size of the received corpus (C.3.lines 50-63-"The number n can either be a predetermined fixed number or a number that dynamically

varies with each language model building iteration. For example n may …", C.6.lines 13-40-his linguistic units as N-items in each subcorpora).

creating the tuning set from application-specific information (C.2.lines 44-48-his restricted corpora, C.5.lines 40-44-the application is speech recognition);

(a) training a seed model via the tuning set (C.6.lines 21-25-his initial reference language model as the seed model);

(b) calculating a similarity within a sequence of the training units on either side of each of the gaps (C.6.lines 34-36-his relevance score calculator of "each unit" inherently includes "on either side of the gap");

(c) selecting segment boundaries that maximize intra segment similarity and inter-segment disparity (C.6.lines 36-41-his threshold comparator and appropriate sub-corpora);

(d) calculating a perplexity value for each segment based on a comparison with the seed model (C.6.lines 28-34);

(e) selecting some of the segments based on their respective perplexity values to augment the tuning set (C.6.lines 30-33-his stored linguistic units);

iteratively refining the tuning set and the seed model by repeating steps (a) through (e) until a threshold (C.6.lines 44-63-"further language building iterations if quality is deemed unsatisfactory"-interpreted to include the above steps as explained); and

refining the language model based on the seed model (C.6.lines 44-63-his new reference language model);

providing a textual corpus comprising subsets wherein each subset comprises a plurality of items.

but lacks explicitly teaching, creating a Dynamic Order Markov Model data structure by assigning each item of the plurality of items to a node in the data structure, wherein the nodes are logically coupled to denote dependencies of the items, and calculating a frequency of occurrence for each item of the plurality of items;

However, Law teaches these limitations, see section 2.2, his hierarchical structure, by classes as subsets-the words as items, and his frequency count, see also sections 2.3-5-as relevant). Therefore it would have been obvious to combine Ramaswamy's segmentation with Law's Dynamic order Markov Modeling (his dynamic N-th order Markov Model),

providing the benefit of modeling un-segmented languages such as Chinese, utilizing a specialized model (see abstract, and section 2.4).

As per **claim 3**, Ramaswamy et al. discloses all of the limitations of claim 1, upon which claim 3 depends. Ramaswamy et al. further discloses:

the tuning set of information is comprised of one or more application-specific documents (C.7.lines 6-9,-the application is e-mail, the documents comprise "show me the next e-mail...")

As per **claim 4**, Ramaswamy et al. discloses all of the limitations of claim 1, upon which claim 4 depends. Ramaswamy et al. further discloses:

the tuning set of information is a highly accurate set of textual information linguistically relevant to (C.2.lines 55-62), but not taken from, the received textual corpus (C.3.lines 14-18, the received corpus-external corpus comprises many domains, however the seed corpus is linguistically related, but not taken from the external corpus).

As per **claim 5**, Ramaswamy et al. discloses all of the limitations of claim 1, upon which claim 5 depends. Ramaswamy et al. further discloses:

a training set comprised of at least the subset of the received textual corpus (C.3.lines 6-8,14-17-test corpus is at least the subset of the received textual corpus).

As per **claim 6**, Ramaswamy et al. discloses all of the limitations of claim 5, upon which claim 6 depends. Ramaswamy et al. further discloses:

ranking the segments of the training set based, at least in part, on the calculated perplexity value for each segment (C.4.lines 36-41, C.6.lines 25-34, C.8.lines 34-36).

As per **claim 14**, Ramaswamy et al. discloses all of the limitations of claim 1, upon which claim 14 depends. Ramaswamy et al. further discloses:

the perplexity value is a measure of the predictive power of a certain language model to a segment of the received corpus (C.4.lines 16-21).

As per **claim 15**, Ramaswamy et al. discloses all of the limitations of claim 1, upon which claim 15 depends. Ramaswamy et al. further discloses:

ranking the segments of at least the subset of the received corpus based, at least in part, on the calculated perplexity value of each segment (C.4.lines 36-40, C.6.lines 25-34, C.8.lines 34, 35); and

updating the tuning set of information with one or more of the segments from at least the subset of the received corpus (C.4.lines 41-47, C.6.lines 37-43).

As per **claim 16**, Ramaswamy et al. discloses all of the limitations of claim 15, upon which claim 16 depends. Ramaswamy et al. further discloses:

one or more of the segments with the lowest perplexity value from at least the subset of the received corpus are added to the tuning set (C.4.lines 41-47- "...below the perplexity threshold...", C.6.lines 37-43).

As per **claim 17** Ramaswamy et al. discloses all of the limitations of claim 1, upon which claim 17 depends. Ramaswamy et al. further discloses:

utilizing the refined language model in an application (C.5.lines 40-42, the application is speech recognition) to predict a likelihood of another corpus (C.5.lines 42-45-the likelihood is interpreted as the "accuracy...for the current language model"-the other corpus is the test corpus).

As per **claim 28**, claim 28 sets forth limitations similar to claim 1, and is thus rejected for the same reasons. Ramaswamy further teaches;

refine the seed model with one or more segments of the received corpus based, at least in part, on the calculated perplexity values (C.4.lines 36-41-his reference model as the seed model);

iteratively refine the tuning set with segments ranked by the seed model (C.4.lines 36-40, C.6.lines 25-34, C.8.lines 34, 35) and in turn iteratively update the seed model via the refined tuning set (C.4.lines 8, 9, 36-47-his "added to relevant corpus", his each time…as the iterations);

filter the received corpus via the seed model to find low-perplexity segments (see claim 16); and

train the language model via the low-perplexity segments (C.6.lines 44-63-his new reference language model);

providing a textual corpus comprising subsets wherein each subset comprises a plurality of items.

but lacks explicitly teaching, creating a Dynamic Order Markov Model data structure by assigning each item of the plurality of items to a node in the data structure, wherein the nodes are logically coupled to denote dependencies of the items, and calculating a frequency of occurrence for each item of the plurality of items;

However, Law teaches these limitations, see section 2.2, his hierarchical structure, by classes as subsets-the words as items, and his frequency count, see also sections 2.3-5-as relevant). Therefore it would have been obvious to combine Ramaswamy's segmentation with Law's

Dynamic order Markov Modeling (his dynamic N-th order Markov Model), providing the benefit of modeling un-segmented languages such as Chinese, utilizing a specialized model (see abstract, and section 2.4).

As per **claim 29**, Ramaswamy et al. discloses all of the limitations of claim 28, upon which claim 29 depends. Ramaswamy et al. further discloses:

the tuning set is dynamically selected as relevant to the received corpus (C.3.lines 47-54).

As per **claim 30**, Ramaswamy et al. discloses all of the limitations of claim 28, upon which claim 30 depends. Ramaswamy et al. further discloses:

a dynamic lexicon generation function, to develop an initial lexicon from the tuning set (C.3.lines 42-44-the tuning set (seed corpus) is used to develop an initial lexicon (corpus)), and to update the lexicon with the select segments from the received corpus (C.3.lines 50-55- "...adding linguistic units to relevant corpus"-the relevant corpus being the updated lexicon).

As per **claim 32**, Ramaswamy et al. discloses all of the limitations of claim 28, upon which claim 32 depends. Ramaswamy et al further discloses:

a dynamic segmentation function (C.5.lines 1-3), to iteratively segment the received corpus (C.5.lines 1-3) to improve a predictive performance attribute of the modeling agent (C.5.lines 6-9-"to improve language model quality..." comprising evaluating perplexity change which is interpreted as the predictive performance).

As per **claim 33**, Ramaswamy et al. discloses all of the limitations of claim 32, upon which claim 33 depends. Ramaswamy et al further discloses:

the dynamic segmentation function iteratively re-segments the received corpus until the language model reaches an acceptable threshold (C.5.lines 1,2, 9-15-the external corpus is segmented, iteratively by extracting linguistic units, until the language model is updated once a "...a certain number..." a threshold is reached).

As per **claim 35**, Ramaswamy et al. discloses all of the limitations of claim 34, upon which claim 35 depends. Ramaswamy et al. further discloses:

the data structure generator removes segments from the data structure that do not meet a minimum frequency threshold (C.4.lines 29-31- it is well known that the relevancy of the segments is based in part on frequency), and dynamically re-segments the received corpus to improve predictive capability while reducing the size of the data structure (C.5.lines 1-3, C.5.lines 6-9-"to improve language model quality…" comprising evaluating perplexity change which is interpreted as the predictive performance).

As per **claims 36 and 43**, Ramaswamy et al. discloses a method of jointly optimizing the performance and size of a language model comprising:

segmenting one or more relatively large language corpora into multiple segments of N items, wherein N is an empirically derived value based, at least in part, on the size of the received corpus (C.3.lines 50-63- "The number n can either be a predetermined fixed number or a number that dynamically varies with each language model building iteration. For example n may …", Fig. 5 item 40', and 41.s.1, 41.s.2…41.s.N, and C.6.lines 15-41-his linguistic units as N-items in each subcorpora).

selecting an initial tuning sample of application-specific data (see claim 1), the initial tuning sample being relatively small in comparison to the one or more relatively large language corpora (C.2.lines 51, 52, C.2.lines 44-63), wherein the initial tuning sample is used for training a seed model (see claim 1-tuning set discussion), the seed model to be used for ranking the multiple segments from the language corpora (see claim 28);

iteratively training the seed model to obtain a mature seed model, wherein the iterative training proceeds until a threshold is reached (see claim 1-each iteration interpreted to be more mature than the first), each iteration of the training including (see claim 1-threshold discussion):

updating the seed model according to the tuning sample (see claim 1-tuning sample as the tuning set);

ranking each of the multiple segments according to a perplexity comparison with the seed model (see claim 28);

selecting some of the multiple segments that possess a low perplexity; and

augmenting the tuning sample with the selected segments (see claims 1 and 28);

once the threshold is reached, filtering the language corpora according to the mature seed model to select low-perplexity segments (see claim 16);

combining data from the low-perplexity segments (see claim 16-adding discussion); and

training the language model according to the combined data (see claim 28-train ...low perplexity discussion).

providing a textual corpus comprising subsets wherein each subset comprises a plurality of items.

but lacks explicitly teaching, creating a Dynamic Order Markov Model data structure by assigning each item of the plurality of items to a node in the data structure, wherein the nodes are logically coupled to denote dependencies of the items, and calculating a frequency of occurrence for each item of the plurality of items;

However, Law teaches these limitations, see section 2.2, his hierarchical structure, by classes as subsets-the words as items, and his frequency count, see also sections 2.3-5-as relevant). Therefore it would have been obvious to combine Ramaswamy's segmentation with Law's Dynamic order Markov Modeling (his dynamic N-th order Markov Model),

providing the benefit of modeling un-segmented languages such as Chinese, utilizing a specialized model (see abstract, and section 2.4).

As per **claim 37**, claim 37 sets forth limitations similar to claim 3 and is thus rejected for the same reasons and under the same rationale.

As per **claim 38**, Ramaswamy teaches 36, and further discloses:

wherein the threshold comprises one of a predetermined sized of the seed model or a sufficient application specificity of the seed model (C.6.lines 44-50-his sufficient number).

As per **claims 39 and 44**, Ramaswamy teaches 36, and further discloses:

pruning the language model utilizing an entropy based cutoff algorithm that uses only information embedded in the language model itself (C.5.lines 6-21-his language model quality criteria and quality determination as the algorithm, his linguistic units as the embedded information).

As per claims 40-42, which depend from claims 1, 28, and 36 respectively, The Examiner takes official notice that pruning a data structure was very well known in the art at the time of the invention. Law further teaches (selectively) pruning the Dynamic Order Markov Model data structure (see section 2.4). Therefore, it would have been obvious to prune

the data structure, which would provide the benefit of using parameterized information.

5. Claims 10-13, 31 and 34 are rejected under 35 U.S.C. 103(a) as being unpatentable over Ramaswamy et al. (U.S. Patent No. 6,188,976 filed Oct. 23, 1998) in view of Law and further in view of Bangalore et al. (U.S. Patent No. 6,317,707 filed Dec. 7,1998).

Ramaswamy et al., Law, and Bangalore et al. are analogous art in that they both deal with language modeling.

As per **claim 10**, Ramaswamy et al. and Law disclose all of the limitations of claim 1, upon which claim 10 depends, but lack explicitly teaching the calculation of the similarity within a sequence of training units defines a cohesion score.

However, Bangalore et al. teaches the calculation of the similarity within a sequence of training units (C.3.lines 22, 23) defines a cohesion score (C.3.lines 15-19 “very close relationship.” is interpreted as the cohesion). Therefore, at the time of the invention, it would have been obvious to one ordinarily skilled in the art to combine Ramaswamy et al. with Bangalore et al. The motivation for doing so would have been to determine how close or similar the training units were to each other for the

benefit of maximizing the clustering process of related items (C.4.lines 12, 13).

As per **claim 11**, Ramaswamy et al. and Bangalore et al. disclose all of the limitations of claim 10, upon which claim 11 depends. Ramaswamy et al. does not disclose:

intra-segment similarity is measured by the cohesion score.

However, Bangalore et al. teaches intra-segment similarity is measured by the cohesion score (C.3.lines 15-19, 22, 23). Therefore, at the time of the invention, it would have been obvious to one ordinarily skilled in the art to combine Ramaswamy et al. with Bangalore et al. The motivation for doing so would have been to measure how close or similar the intra-segment training units were to each other for the benefit of maximizing the clustering process of related items (C.3.lines 17-19, C.4.lines 13, 14), to better improve subsequent language modeling results.

As per **claim 12**, Ramaswamy et al. Law, and Bangalore et al. disclose all of the limitations of claim 10, upon which claim 12 depends. Ramaswamy et al. and Law do not disclose:

inter-segment disparity is approximated from the cohesion score.

However, Bangalore et al. teaches inter-segment (C.3.lines 24, 25- the different vector coordinates interpreted inter-segments) is approximated form the cohesion score (C.4, lines 35-45, Table 2-the "Compactness Value"-determines the score and cohesion and the "Class Index"- determines the inter-segment disparity resulting from the cohesion score). Therefore, at the time of the invention, it would have been obvious to one ordinarily skilled in the art to combine Ramaswamy et al. with Bangalore et al. The motivation for doing so would have been to determine how disparate or distinct the inter-segment training units were to each other for the benefit of maximizing the clustering process of related items (C.3.lines 15-19, C.4.lines 14, 15), to better improve subsequent language modeling results.

As per **claim 13**, Ramaswamy et al., and Law disclose all of the limitations of claim 1, upon which claim 13 depends. Ramaswamy et al. and Law do not disclose:

the calculation of inter-segment disparity defines a depth score.

However, Bangalore et al. teaches the calculation of inter-segment disparity defines a depth score (C.4.lines 12-16, 30-66-Table 2 the depth of the inter-segment disparity approximated form the cohesion score-

compactness value- is indicated as the values are "deeper" as they are farther down the list). Therefore, at the time of the invention, it would have been obviousness to one ordinarily skilled in the art to combine Ramaswamy et al. with Bangalore et al. The motivation for doing so would have been to determine the depth of the disparity in a ranked manner to visually determine the relatedness of different classes or inter-segment disparity by index (C.4.Table 2-visual depth benefit).

As per **claim 31**, Ramaswamy et al. an law disclose all of the limitations of claim 28, upon which claim 31 depends, but lack explicitly teaching:

a frequency analysis function, to determine a frequency of occurrence of segments within the received corpus.

However, Bangalore et al. teaches having a function based upon frequencies for each input word, which determines the frequencies of segments within the received corpus (C.3.lines 45-47). Therefore, at the time of the invention, it would have been obvious to one ordinarily skilled in the art to combine Ramaswamy et al. with Bangalore et al. The motivation for doing so would have been to assist in building a cluster in the well known method of having a vector space to hold the clusters with the

frequency of each segment being incorporated into the cluster for the benefit of maximizing the clustering segments (C.3.lines 18-20, 62, 63, C.4.lines 13, 14), to better improve subsequent language modeling results.

As per **claim 34**, Ramaswamy et al. and Law disclose all of the limitations of claim 32, upon which claim 34 depends, but lack explicitly teaching:

a frequency analysis function, to determine a frequency of occurrence of segments within the received corpus.

However, Bangalore et al. teaches having a function based upon frequencies for each input word, which determines the frequencies of segments within the received corpus (C.2.lines 59, 60). Therefore, at the time of the invention, it would have been obvious to one ordinarily skilled in the art to combine Ramaswamy et al. with Bangalore et al. The motivation for doing so would have been to assist in building a cluster in the well known method of having a vector space to hold the clusters with the frequency of each segment being incorporated into the cluster for the benefit of maximizing the clustering segments (C.3.lines 18-20, 62, 63, C.4.lines 13, 14), to better improve subsequent language modeling results.

Conclusion

6. Applicant's amendment necessitated the new ground(s) of rejection presented in this Office action. Accordingly, **THIS ACTION IS MADE FINAL**. See MPEP § 706.07(a). Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the date of this final action.

7. Any inquiry concerning this communication or earlier communications from the examiner should be directed to Lamont M. Spooner whose telephone number is 571/272-7613. The examiner can normally be reached on 8:00 AM - 5:00 PM.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Richemond Dorvil can be reached on 571/272-7602. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

Information regarding the status of an application may be obtained from the Patent Application Information Retrieval (PAIR) system. Status information for published applications may be obtained from either Private PAIR or Public PAIR. Status information for unpublished applications is available through Private PAIR only. For more information about the PAIR system, see http://pair-direct.uspto.gov. Should you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free).

lms
10/23/06

A.k. Azad 10/27/06

ABUL AZAD
PRIMARY EXAMINER